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National soil organic carbon estimates can improve global estimates

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ABSTRACT

Global inventories of spatial and vertical distribution of soil organic carbon (SOC) stocks are being used in national and global initiatives targeted to mitigate climate change and land degradation impacts. Yet, national level high-resolution estimates of SOC stocks can be useful for improving the accuracy of global SOC inventories. We estimated spatially resolved SOC stocks of surface 0–30 cm and subsurface 30–100 cm layers at a spatial resolution of 30 m in tropical Island, Sri Lanka using a legacy harmonized soil database of 122 soil profiles. The national estimates were compared with two global estimates derived from WISE30sec and SoilGrids250m. The tropical Island (land area = 64,610 km^2) occupying 0.03% of global land area showed a considerable heterogeneity in SOC stocks ranging from 2.0–342.5 Mg ha^{-1} and 2.7–391.7 Mg ha^{-1} in the surface and subsurface soil layers, respectively. We found, elevation, precipitation and slope angle as main environmental controllers of the spatial distribution of SOC stocks under tropical climate. Incorporating the pedogenic information (derived from soil series level legacy map, soil orders and suborders) with environmental controllers resulted in better regression models of predicting surface ($R^2 = 0.61$) and subsurface ($R^2 = 0.81$) SOC stocks. Geographically weighted regression kriging derived maps of SOC stocks revealed that 0–100 cm soil layer of the tropical Island stored 500 Tg C contributing for 0.04% of the global SOC stocks. The validation results of our estimates showed low Mean Estimation Error (MEE: surface −1.6 and subsurface −1.6 Mg ha^{-1}) and Root Mean Square Error (RMSE: surface 29.5 and subsurface 24.9 Mg ha^{-1}) indicating a low bias and satisfactory predictions. The relative improvement of the prediction accuracy of the SOC stocks of our geospatial estimates in the 0–30 cm layer in comparison to SoilGrids250m and WISE30sec data derived SOC stocks were 51.7% and 35.2%, respectively. The SOC stocks predictions of the 30–100 cm soil layer showed even better relative improvement compared to SoilGrids250m (78.4%) and WISE30sec (57.4%) SOC estimates. Compared to estimates of total SOC stocks resulted in this study, WISE30sec data derived SOC stock maps showed 30% over estimation of the C stock in surface 0–30 cm (332 Tg C) and 41% overestimation in 30–100 cm layer (343 Tg C). The over estimation of total SOC stocks by the SoilGrids250 SOC stocks map for the surface 0–30 cm layer was 122% (567 Tg C) and for the 30–100 cm layer it was 209% (750 Tg C). We conclude that the fusion of legacy soil information of SOC stocks with appropriate environmental covariates and pedogenic information derived from legacy area-class soil maps at national level can produce more accurate inventories of spatial and vertical distribution of SOC stocks. These national inventories have a great potential of upgrading global inventories of SOC stocks.

1. Introduction

Soils constitute the Earth's largest terrestrial carbon (C) pool, and their responsiveness to land use and management make them appealing targets for strategies to enhance C sequestration (Nave et al., 2018). Soil organic carbon (SOC) stocks and fluxes are soil- and site specific and reflect the long-term balance between organic matter inputs from vegetation and losses due to decomposition, erosion, and leaching. Current estimates suggest that soils to 1 m depth hold 74% of the total terrestrial C stocks (Batjes, 2016; Köchy et al., 2015; Scharlemann et al., 2014). Given the significance of this proportion, and the realization that increasing SOC stocks by even a few percent translates into globally relevant magnitude of C, quantifying the spatial heterogeneity of SOC stocks and its environmental controllers is important.

Many global initiatives targeted to mitigate climate change and land degradation impacts are relying on accurate and detailed inventories of SOC at (sub) national levels. The concept of '4 per mille' is one of such optimistic initiative aiming an annual increase of SOC stocks by 0.4% (Lal, 2016; Minasny et al., 2017). Achieving Land Degradation Neutrality (LDN) in 2030 (United Nations General Assembly, 2015), as

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implemented by the United Nations Convention to Combat Desertification (UNCCD) also partly relied on monitoring of soil quality indicators including SOC. Detailed spatial inventories of forest SOC stocks and establishing observational networks (Vitharana et al., 2017) for monitoring are prerequisites for C credit initiatives. Moreover process based models such as RothC (Coleman and Jenkinson, 1996) and CENTURY (Parton et al., 1987) used for predicting carbon fluxes, play a major role in providing information of land use and climate change impacts on SOC stocks. The results of these and other land surface models depend on soil and site-specific information of SOC stocks, input of litter to the soil, and the changes in the amount of soil carbon over time. In order to address these data needs, a substantial attention has been drawn to quantify the SOC stocks at regional, national and global scales and monitoring temporal changes in these stocks.

Many global soil information systems such as harmonized world soil data base (HWSD), Soil and terrain database (SOTER) and the Soil Profile Analytical Database for Europe (SPADE) are available for wide range of applications including modeling of SOC stocks and estimating C sequestration potentials. Batjes (1996) estimated the global SOC stocks using the World Inventory of Soil Emissions Potentials (WISE) soil data base (4353 profiles). More recently, Batjes (2016) produced a more comprehensive estimates of global SOC stocks using WISE30sec data set which is a harmonized data product (grid cell size 0.86 km^2) of soil properties derived using map unit delineations of HWSD, Köppen-Geiger climatic zones and ISRIC-wise soil profile data including nearly 21,000 profiles. Hengl et al. (2017) argued that data bases such as WISE30sec that uses discrete representation of spatial variability are less suited for use in many of the (global) simulation models and decision making systems. Global Soil Information Facilities (GSIF) is a cyber-infrastructure for storing georeferenced soil profile descriptions with associated analytical data and for supporting the production of digital soil maps from global to regional scales. Hengl et al. (2014) used digital soil mapping techniques to produce global spatial inventory of SOC stock at a resolution of 1 km (SoilGrids1km). Later, more detailed (spatial resolution 250 m) 3D global inventory of SOC stocks, SoilGrids250m (Hengl et al., 2017) was generated and embedded in the GSIF facilities. Though, such global data sets have considerable potentials in improving global soil carbon flux estimates under changing climate, these datasets have their own inherent deficiencies. The global prediction models used in constructing such data sets may not be able to capture the local and regional heterogeneity resulted by complex interaction of environmental controllers. Often, soil profile data used in the global soil mapping efforts are collected over different time periods and using a variety of soil analytical methods. Thus, lack of harmonization between soil profile data may lead to unreliable estimates. Batjes (2016) reported that global soil profile data sets have uneven spatial distributions causing many geographic gaps. These limitations inherent in soil information can be attributed to the institutional limitations to share soil data. Moreover, while handling global soil profile databases, the contribution of local expertise at national level is often neglected. This has avoided the use of expert judgment on the numerical and spatial accuracy of profile data. Further, inputs from pedologists can be of great importance to identify country specific environmental covariates such as legacy soil maps and national agro-climatic data. Stockmann et al. (2013) discussed the uncertainty associated with global SOC stock estimates and reported that estimates of SOC pool to 1 m depth varies between 1463 and 2011 Pg C. Therefore, development of (sub) national level data bases of SOC stocks has been progressed in parallel to global attempts; Chile (Padarian et al., 2017), Australia (Viscarra Rossel et al., 2014), Tanzania (Winowiecki et al., 2016), Nigeria (Akpa et al., 2016), China (Wang et al., 2004), Belgium – crop lands and grasslands (Meersmans et al., 2011), Alaska (Mishra et al., 2017; Mishra and Riley, 2012), United Kingdom (Bradley et al., 2005), Denmark (Adhikari et al., 2014), USA (Odgers et al., 2012), Scotland (Poggio and Gimona, 2014), France (Mulder et al., 2016), and Canada (Tarnocai, 1998).

Tropical landmass that is distributed about 25 degrees north and south of the Equator is a significant contributor for global SOC sequestration capacity. Tropical soils contain about 26% of the soil organic carbon (SOC) stored in the soils of the world (Batjes, 1996). Lal (2005) estimated 30.3% of the global forest C stock is stored in tropical forests. However, many tropical countries are lacking with national SOC inventories mainly due to limitations of soil data. For an example, apart from few local and regional mapping efforts on spatial heterogeneity of soil C in Sri Lanka (e.g., Ratnayake et al., 2016), national scale SOC inventory is yet to be developed. However, Sri Lanka is among the first Asian nations to develop national level soil inventories (Young, 2017) using traditional soil surveying approaches. Thus, these area-class soil maps enriched with pedological knowledge could serve as legacy information for digital mapping of SOC stocks. The most updated soil spatial inventory consists of soil series level map and a profile data base of 122 profile information (Mapa, 2016; Mapa et al., 1999, 2005, 2010). We hypothesized that the use of limited but harmonized database of soil profiles in combination with legacy soil geographic map units and appropriate environmental controllers, can lead to generation of spatially-explicit estimates of SOC stocks, which could be more accurate in comparison to global estimates of SOC stocks. Our objectives in this study were to (1) elucidate environmental controllers of SOC stocks and create a high resolution (30-m spatial resolution) estimate of SOC stocks for surface and subsurface soils of Sri Lanka, and (2) use these estimates to evaluate the prediction accuracy of global SOC estimates in representing Sri Lankan SOC stocks.

2. Materials and methods

2.1. Study area

Soil organic carbon (SOC) stocks were spatially predicted at 30-m spatial resolution for the entire Sri Lanka, South Asian Island which occupies a land area of 64,610 km^2. Sri Lanka is a tropical Island which has a variety of climatic conditions due to its geographical setting. The average annual precipitation varies from 900 mm in driest parts to 5400 mm in wettest parts resulted by a location dependent bi-modal or uni-modal rainfall distribution (Chandrapala, 1997). Being an island situated in low latitudes between 6 and 10° N, Sri Lanka has typical maritime-tropical temperatures, greater daily than annual temperature ranges. The mean annual temperature depends on the altitude of a location and ranges from 27 °C in coastal lowlands to 16 °C in central highlands. The spatial heterogeneity of topography and climatic conditions in this tropical Island has resulted in a considerable variability of the soil properties.

2.2. National soil carbon database

We used 110 georeferenced benchmark soil profile data from the SRICANSOL project soil profile database (Mapa et al., 1999, 2005, 2010). This is the latest and most comprehensive legacy soil profile database of Sri Lanka which contains soil profile descriptions and soil physicochemical properties characterizing 110 soil series of Sri Lanka. Additionally, recently inventoried database of 12 georeferenced bench mark soil profiles (Mapa, 2016) were included to represent the soils of Northern region of Sri Lanka, which was not covered under the SRICANSOL project. The Sampling locations across Sri Lanka are shown in Fig. 1. These benchmark soil profile data collection efforts used expert knowledge based targeted sampling approach to capture different soil types, and identical field and laboratory analyses methods were adopted to create a harmonized soil data base for the country. Profile data set (n = 122) includes organic carbon (OC%) and bulk density ($Mg\,m^{-3}$) measurements from each soil horizon determined using Walkley and Black (Grossman and Reinsch, 2002; Walkley and Black, 1934) and core sample methods, respectively. Walkley and Black (1934) reported a recovery of 60 to 86% of C for the wet digestion

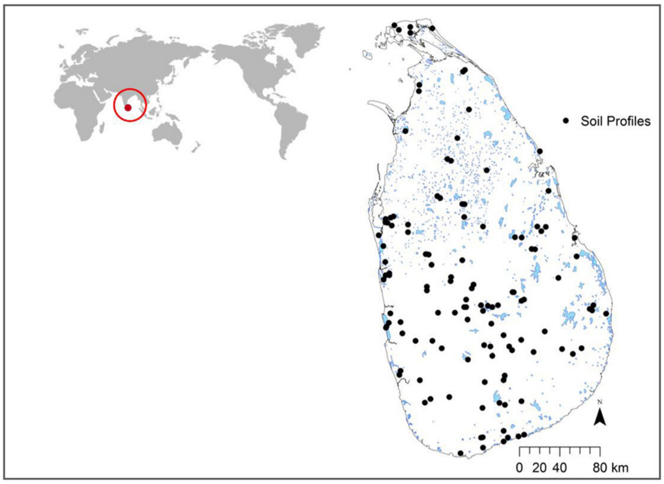

Fig. 1. Locations of benchmark soil profiles (black dots) in the study area. The inset shows location of Sri Lanka in the Global map and blue color polygons represent water bodies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

method. Therefore, underestimation of SOC stocks is expected. Mass-preserving depth splines (Bishop et al., 1999) were fitted to soil profile data to estimate average values of OC% and bulk density for depth intervals, 0–30 and 30–100 cm. This approach of calculating soil properties for predefined depth intervals and has been adopted in several digital soil mapping studies (Malone et al., 2009; Odgers et al., 2012; Poggio and Gimona, 2014). However, bulk density data were missing for horizons of few profiles. Thus, we used bulk density, soil texture and OC data of two depth intervals to develop a pedotransfer function to estimate missing bulk density values. The data set (n = 226) was partitioned into a training (n = 151) and a validation (n = 75) data sets. The Conditioned Latin Hypercube sampling method was used for partitioning data sets representing the variability of bulk density values. The regression analysis resulted in the following pedotransfer function (R^2 = 0.70):

$$\text{Bulk density (Mg m}^{-3}) = 1.4 + 0.003\ \text{sand\%} + 0.001\ \text{silt\%} - 0.004\ \text{clay\%} - 0.049\ \text{OC\%} \tag{1}$$

Lower values of mean estimation error (MEE = 0.02 Mg m^{-3}) and root mean square error (RMSE = 0.16 Mg m^{-3}) showed an acceptable prediction accuracy of the pedotransfer function (1).

Soil carbon stocks of two depth intervals were computed using following equation:

$$\text{SOC} = \rho_b \times \text{C} \times \text{T} \times 100 \tag{2}$$

where, SOC is the soil carbon stock (Mg C ha^{-1}), ρ_b is the soil bulk density (Mg m^{-3}), and C and T are organic carbon (%) and the thickness of the soil depth interval (m), respectively. We predicted SOC stocks for surface 30 cm and 30–100 cm depths.

2.3. Soil and environmental covariates of the study area

We investigated the potential of using legacy soil information (descriptions of soil series across study area) and environmental covariates as spatial predictors of SOC stocks of the Island. Legacy soil information layers were derived from the soil maps of the Wet Zone (Mapa et al., 1999), Intermediate Zone (Mapa et al., 2005), Dry Zone (Mapa et al., 2010) and the North-Eastern region of Sri Lanka (Mapa, 2016) covering the entire country. These maps were generated at soil series level and each series was classified at family level of soil taxonomy (Soil Survey Staff, 2014). Based on Soil Taxonomic names, we aggregated mapping units of soil series into soil orders and suborders. This aggregation of taxonomic classes resulted into 14 suborders and seven orders ranging from relatively young Inceptisols to highly weathered Ultisols.

A digital elevation model (DEM) of 30 m spatial resolution was obtained from the NASA Shuttle Radar Topography Mission (SRTM) database (Farr et al., 2007). The pit filled DEM was used to derive primary and secondary terrain attributes those are known to control spatial distribution of SOC stocks (Mishra et al., 2017; Mishra and Riley, 2012, 2015). Terrain analysis was performed using spatial analyst tool of ArcGIS version 10.4.1 (Environmental Systems Research Institute, Inc., Redlands, CA, USA). Primary terrain attributes include elevation and slope and secondary terrain attributes include specific catchment area (A_s m^2 m^{-1}), soil wetness index (SWI) and sediment transport index (STI). A_s represents the cumulative upslope area per unit width of contour and it reflects the degree of surface runoff (Wilson and Gallant, 2000). SWI reflects the tendency of surface water flow to accumulate at any point in a catchment and is calculated as a ratio between the A_s and slope gradient in degrees (β) (Wilson and Gallant, 2000):

$$\text{SWI} = \left(\frac{A_s}{\tan\beta}\right) \tag{3}$$

Sediment transport index is a measure of the soil loss potential by water erosion and calculated as (Wilson and Gallant, 2000):

$$\text{STI} = \left(\frac{A_s}{22.13}\right)^{0.6}\left(\frac{\sin\beta}{0.0896}\right)^{1.3} \tag{4}$$

We extracted the long-term (1950–2000) mean annual air temperature and precipitation data of 1 km spatial resolution from the global climate surfaces (Hijmans et al., 2005).

Normalized difference vegetation index (NDVI) data at 30 m spatial resolution was calculated using bands 4 (red) and 5 (near infrared) of the Landsat 8 image collected from the image inventory of USGS Earth Explorer (earthexplorer.usgs.gov: verified on 20th August 2017). Cloud and cloud shadow in each image was detected and corrected using ERDAS Imagine 9.1 (ERDAS Atlanta, GA, USA) software. Subsequently, reflectance at red (ρ_{red}) and near infrared bands (ρ_{nir}) was computed. The NDVI of a pixel was computed as:

$$\text{NDVI} = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{5}$$

Land cover data of Sri Lanka at 250 m spatial resolution were extracted from European Space Agency, the Climate Initiative land cover project database (www.esa-landcover-cci.org: verified on 20th March 2018). To represent the land cover during the soil survey period (1999–2010), annual global land cover for the year 2005 was extracted and the land cover types distributed throughout the country were reclassified into 10 categories. Major categories of land cover types were croplands and grasslands (43.5%) which was followed by forest (33.1%) and shrublands (12.2%). All the environmental covariates data used in this study were resampled to a common spatial resolution of 30 m for further analysis using spatial analyst function of ArcGIS version 10.4.1 (Environmental Systems Research Institute, Inc., Redlands, CA, USA).

2.4. Spatial prediction of soil organic stocks and prediction accuracy

We used a geographically weighted regression kriging approach (Kumar et al., 2012) to produce SOC stock estimates for the study area. In this approach, instead of using a global regression model as in case of regression kriging (Hengl et al., 2007) approach, we used the Geographically weighted regression (GWR) (Fotheringham et al., 2002; Mishra et al., 2010a; Mishra and Riley, 2014, 2015) to create regression predicted SOC stocks. Local spatial prediction models such as GWR often showed its merits over global regression methods in better representing the spatial heterogeneity and environmental controllers of SOC stocks (Mishra et al., 2017; Zhang et al., 2011). A GWR model (Fotheringham et al., 2002) can be written as:

$$\hat{SOC}_i = \hat{\beta}_0(u_i, v_i) + \hat{\beta}_1(u_i, v_i)X_{i1} + \hat{\beta}_2(u_i, v_i)X_{i2} + ... + \hat{\beta}_k(u_i, v_i)X_{ik} \quad (6)$$

where the predicted SOC stock at i^{th} location is given by $\hat{SOC}_i$, (u_i, v_i) denotes coordinates of i^{th} location, $\hat{\beta}_0$ and $\hat{\beta}_1$, …, $\hat{\beta}_k$ are regression coefficients pertaining to relevant k number of covariates X_{i1}, …, X_{ik} at i^{th} location. In GWR a weighting function is applied to assign greater influence of observations near to the prediction point. In this study adaptive kernel type weighting function was used, thus the spatial context of GWR model fitting is a function of the density of neighboring observations. Akaike Information Criterion (Fotheringham et al., 2002), was used to determine the band width distance. The GWR parameters were predicted at a regular grid of 30 m using GWR tool available in spatial statistics tools of ArcGIS version 10.4.1 (Environmental Systems Research Institute, Inc., Redlands, CA, USA).

We used multiple linear regression based on ordinary least square estimation of coefficients to select statistically significant environmental controllers of the SOC stocks. Categorical variables, i.e. soil orders, suborders, land cover types were converted to dummy variables and included in the regression analysis. The stepwise regression was performed using PASW Statistics 18 software (SPSS Inc., Chicago, IL, USA). The selected model was tested for the multicollinearity of covariates and randomness of residuals. The residuals from the GWR model were spatially autocorrelated. Therefore, the GWR residuals were spatially interpolated using ordinary kriging and added to the GWR predictions. The latter approach is popularly known as regression kriging (Hengl et al., 2007) and used for optimizing spatial predictions. SOC stock estimates were generated for two depth intervals (0–30 cm, 30–100 cm), in which 0–30 cm layer is the default soil depth considered in IPCC greenhouse gas inventories (IPCC, 2006).

2.5. Accuracy of soil organic carbon stocks prediction

We used cross-validation approach (Isaaks and Srivastava, 1989) to assess the accuracy of predicted SOC stocks for both surface 30 cm and 30–100 cm soil layers. Cross-validation, which is also referred to as "leave-one-out validation approach" removes one observation and estimates the value of SOC stocks at that location with the remaining observations. Thus, the regression kriging approach was run for 122 times to generate the validation data set for every sampling location. In addition, we also compared our predictions with two recent global predictions of SOC stocks namely, SoilGrids250m version 0.5.8 (Hengl et al., 2017) and WISE30sec GIS-data base version 1 (Batjes, 2016). Organic Carbon stock estimates were downloaded via http://soilgrids.org to construct maps representing SoilGrids250m initiative. Wise30Sec data of organic carbon content and bulk density for depth layers D1 to D5 were downloaded via ISRIC's soil data hub (http://www.isric.org/explore/wise-databases) and SOC stocks of soil layers, 0–30 cm and 30–100 cm were calculated considering the full map unit composition (Batjes, 2015). The SOC stock values from these two global estimates were extracted at 122 benchmark profiles for both surface 30 cm and 30–100 cm depths. Two validation indices, namely mean estimation error (MEE) and root mean square error (RMSE) were computed to assess prediction accuracies of all three predictions:

$$\text{MEE} = \frac{1}{n}\sum_{i=1}^{n}[\text{SOC}(x_i) - \hat{\text{SOC}}(x_i)] \quad (7)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[\text{SOC}(x_i) - \hat{\text{SOC}}(x_i)]^2} \quad (8)$$

where, SOC(x_i) is the measured SOC, $\hat{\text{SOC}}(x_i)$ the estimated SOC stocks at i^{th} location, and n is the number of ($n = 122$) validation observations. These values should approach zero for accurate predictions.

The relative improvement (RI) of prediction accuracy of the SOC stocks map produced in this study over SoilGrids250m and WISE30sec GIS-data base were calculated using:

$$\text{RI} = \frac{RMSE_{GD} - RMSE_{SL}}{RMSE_{GD}} \quad (9)$$

where $RMSE_{GD}$ and $RMSE_{SL}$ are the root mean square errors of the given global soil data set and the map produced in this study, respectively.

2.6. Spatial uncertainty of predicted SOC stocks

Digital soil mapping involves the use of empirical prediction models and a variety of data sources to make spatially-explicit predictions of soil properties. Thus, the predictions are always associated with uncertainties arising from different data sources. We assumed that in our case, the uncertainties from different sources will be represented in the model residuals. Therefore, we quantified the uncertainty of SOC stock predictions of by using the normally distributed model residuals (Heuvelink, 2017; Mishra et al., 2017). The uncertainty of GWR prediction is represented by the stochastic residuals (ε) of predictions. Thus, ε values of GWR predictions were calculated by:

$$\varepsilon_i = \hat{\text{SOC}}_i - \text{SOC}_i \quad (10)$$

where, ε_i, $\hat{\text{SOC}}_i$ and SOC$_i$ are the residuals, predicted SOC stock and actual SOC stock at i^{th} location, respectively. Maps of the standard errors were produced for both depth intervals using the simple kriging function of Geostatistical Analyst tool of ArcGIS version 10.4.1. The prediction standard error was multiplied by 1.96, the z value that corresponds to 95% probability. The resultant confidence interval map was added and subtracted from the GWR predicted SOC stock map to derive the 95% upper and lower prediction limits, respectively. The uncertainty quantification approach that we used can be summarized in the equations below:

$$PL_i^L = Pr_i - 1.96 * \text{PSE} \quad (11)$$

$$PL_i^U = Pr_i + 1.96 * \text{PSE} \quad (12)$$

where PL_i^L and PL_i^U are the lower and upper prediction limits of SOC stocks for selected depth interval at the i^{th} observation, respectively, Pr_i is the model prediction of SOC stocks at the i^{th} observation, 1.96 is the Z value at 95% probability, and PSE is the prediction standard error of the residuals.

3. Results

3.1. Summary statistics of SOC stocks and its environmental controllers

Summary statistics of SOC stocks and environmental covariates at soil profile observation sites are shown in Table 1. The SOC stocks data at both surface and subsurface soil layers showed unimodal distribution but were positively skewed (skewness = 3.5 and 3.8, respectively). SOC stocks of both depth intervals showed few extremely high values ($n = 5$, SOC stock > 200 Mg ha^{-1}), these soil profiles were distributed in high elevated areas where cold climate is present, and in low lying south western part of Sri Lanka where marshy wetlands are located. As these extreme values were associated with topographic and environmental conditions, we retained these observations for further analysis. Large variations of SOC stocks in top 30 cm (range = 340.6 Mg ha^{-1}) and 30–100 cm depths (range = 389 Mg ha^{-1}) were observed. Heterogeneity in climatic, topographic and bedrock geology types governed the observed spatial heterogeneity in SOC stocks. The median values of SOC stocks of the surface and subsurface soils were 35.3 Mg ha^{-1} and 32.1 Mg ha^{-1}, respectively.

3.1.1. Topography

Fig. 2a shows the distribution of SOC stocks in three elevation zones of Sri Lanka (Panabokke, 1996), low country (< 300 m), mid country (300–900 m) and up country (> 900 m). We observed distinct differences in SOC stocks between these three elevation zones. Surface soil

Table 1
Descriptive statistics of SOC stocks observations (n = 122) of 0–30 cm and 30–100 cm soil layers and values of some co-located environmental covariates.

Statistic	SOC stock 0–30 cm	SOC stock 30–100 cm	Elevation	Slope	Precipitation	Temperature
	Mg ha^{-1}	Mg ha^{-1}	m	°	mm	°C
Min.	2.0	2.7	5	0.5	940	14.9
Max.	342.5	391.7	2090	50.5	4033	28.0
Mean	47.2	47.0	208.6	8.6	1458.5	26.3
Median	35.3	30.4	60.5	5.8	1458.5	27.1
SD	46.7	54.2	367.7	8.3	653.6	2.3
CV, %	99	115.3	176.3	96.3	44.8	8.7
Skewness	3.5	3.8	2.9	2.4	1.6	−2.8

layer of the up country contained 2.7 and 1.8 times more SOC in comparison to low country and mid country, respectively. This trend of SOC distribution across elevation zones was also observed for the SOC stocks of the sub-surface soil layer. The low country that occupies majority of land mass (86.2%) except the central part of the Island, showed the lowest SOC storage with average SOC stocks of 40.8 and 42.5 Mg ha^{-1} in surface 30 cm and 30–100 cm soil layers, respectively. The surface and subsurface SOC stock in the up country of the Island representing the central highlands showed the largest averages (110.7 and 109.7 Mg ha^{-1}, respectively) and the mid country showed intermediate values (60.0 and 50.1 Mg ha^{-1}, respectively). This indicated that elevation is one of the strongest controller of SOC stocks across the tropical Island. In the low country areas of Southwest to Southern border of the Island, where poorly drained bog soils (Taxonomic equivalent: Histosols) are distributed (Panabokke, 1996) contained high surface and subsurface SOC stocks. Moreover, some locations in the mid country, which receives high rainfalls, showed high values of surface C stocks.

3.1.2. Temperature and rainfall

The mean annual surface air temperature across the tropical Island mainly depends on the altitude of a location. Low lying coastal areas have an average temperature of 27 °C and the temperature decreases rapidly with increasing altitude towards the central highlands of the

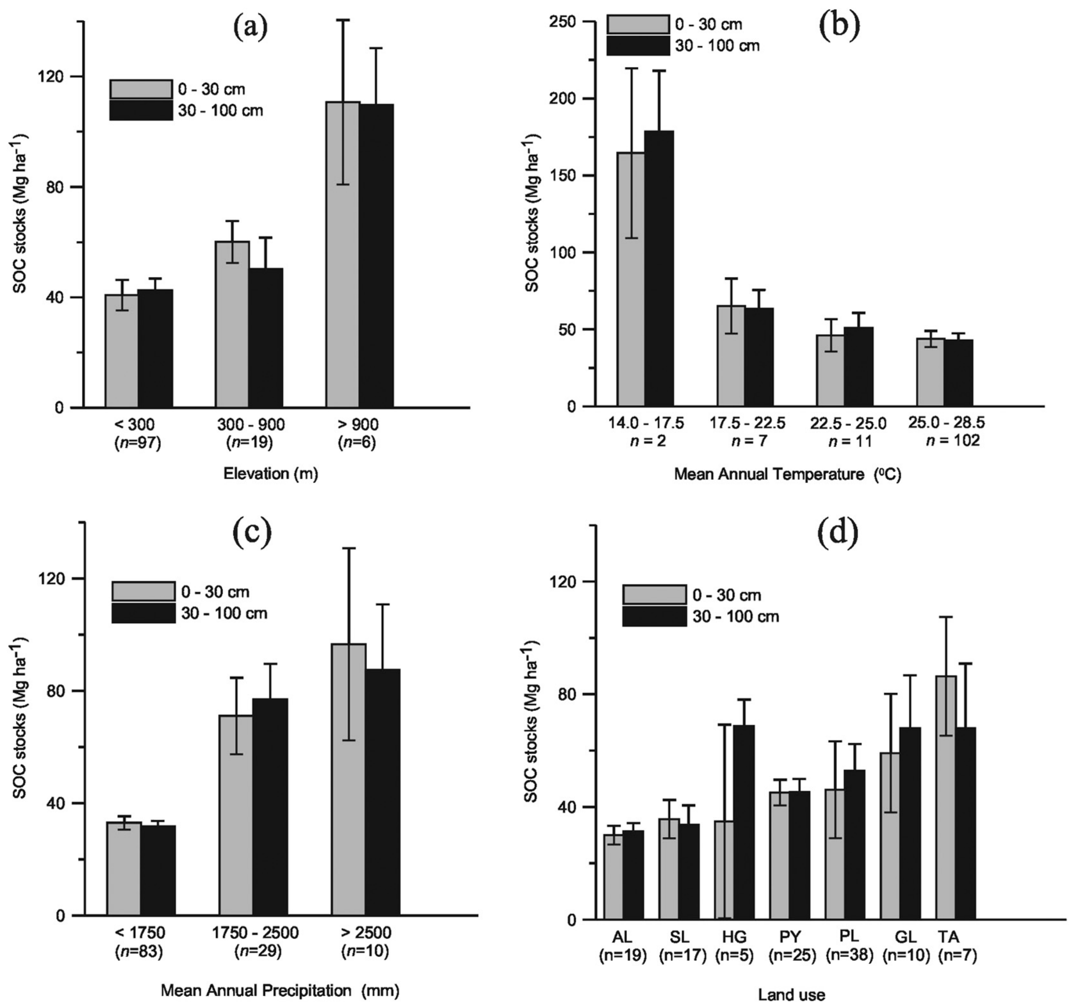

Fig. 2. Average soil organic C stocks in surface 30 cm and 30–100 cm soil layers in relation to (a) elevation, (b) mean annual temperature, (c) mean annual precipitation and (d) land use. Error bars show standard error values, land use categories; AL-Annual crops, SL = Shrub lands, HG-Home Gardens, PY = Paddy, PL = perennial crops, GL = Grass Lands and TA = Tea.

Island. In central parts of the Island, at an altitude of 500 m the average temperature is 20 °C and at highland areas (> 1889 m) it decreases to 16 °C. Fig. 2b shows the average surface and subsurface SOC stocks in areas of different mean annual temperatures. These temperature classes were modified from Panabokke (1996) on the basis of the distribution of soil profiles. As temperature decreases from 28.5 °C in low lands to 14 °C in highlands, the average surface and subsurface SOC stocks increase from 43.5 to 164.5 Mg ha^{-1} and 42.9 to 178.4 Mg ha^{-1}, respectively. Fig. 2c shows surface and subsurface SOC stocks in three distinct rainfall zones of Sri Lanka. The dry zone, which receives mean annual rainfall of < 1750 mm showed the lowest SOC stocks. The dry zone of Sri Lanka occupies large landmass of the country (60%) covering northern and eastern parts of the country. The wet zone is distributed over the southwestern part of the country (20%) including the central hill-country and it receives a relatively high mean annual rainfall of over 2500 mm without distinct dry periods. The highest SOC stocks were observed in the wet zone. The intermediate zone, which receives a mean annual rainfall in between 1750 and 2500 mm, showed comparatively less SOC stocks in comparison to the wet zone. We noticed comparatively less variation of SOC stocks in the Dry Zone. This coincides with relatively less spatial and temporal variation of precipitation in the Dry Zone.

3.1.3. Land use

Site descriptions of soil profile database were classified into seven land use categories. Among these land uses, tea grown soils showed the highest SOC stocks; 86.3 and 67.8 Mg ha^{-1} in 0–30 cm and 30–100 cm soil layers, respectively. Tea plantations occupy 3.5% of the land cover of the Island (Department of Census and Statistics, Sri Lanka, 2016) and mainly distributed in the wet and intermediate zones where the SOC stocks are higher (Fig. 2c). Thus, favorable climatic conditions could be an underlying reason for higher SOC observed in tea grown soils. However, depletion of SOC stocks on tea lands in Sri Lanka can be more severe because of soil erosion triggered by steep topography of landscapes under tea plantations, poor soil management and poor vegetation cover in seedling tea (tea propagated from seeds). Followed by tea plantations, grasslands and perennial crops (Rubber and Coconut) occupying 8.4% of the land area (Department of Census and Statistics, Sri Lanka, 2016) showed higher SOC stocks. Paddy lands of Sri Lanka are distributed in the dry, intermediate and wet zones occupying 12.3% of the land area. Compared with native grasslands, paddy lands showed lower SOC stocks; 46.1 and 52.8 Mg ha^{-1} in 0–30 cm and 30–100 cm soil layers, respectively which is comparable to SOC stocks under perennials. We found that 79% of sampled paddy lands were distributed in the drier part of the country (mean annual rainfall of < 1750). In addition to climatic conditions, continuous disturbance of the soil due to plowing can cause comparatively lower SOC stocks in paddy soils. In Sri Lanka 16.7% of land area is covered with home gardens (Department of Census and Statistics, Sri Lanka, 2016). We observed a large heterogeneity of surface soil C stock possibly due to diversity of vegetation cover among home gardens. However, the subsurface soils under home gardens showed the largest SOC stocks among all land uses. The lowest SOC stock was found on annual croplands those are subjected to continuous tillage and lack of crop residue management.

3.2. Spatial prediction models of SOC stocks

Environmental covariates for spatial prediction of SOC stocks were chosen through the stepwise multiple linear regression (MLR). Table 2 shows selected MLR models and their parameters. Variance inflation factors (VIF) calculated for the selected models revealed an absence of multicollinearity among selected covariates (VIF < 3).

The coefficient of determination values of MLR models for surface and subsurface SOC stocks, $R^2 = 0.61$ and $R^2 = 0.81$, respectively showed a significant control of selected predictors on SOC stocks. Considerable variation of surface SOC stocks (61%) was explained by elevation, precipitation, and soil types (Histosol soil order and the Aquent suborder). Elevation, slope, soil orders (Histosol and Ultisol), and suborder Aquent explained 81% of the SOC stock variability in the subsurface layer (30–100 cm).

Table 2
Multiple linear regression prediction models for SOC stocks of 0–30 cm and 30–60 cm soil layers and coefficient estimates (n = 122).

Predictor	Model coefficient
Soil layer: 0–30 cm	
Intercept	7.27
Elevation	0.42
Precipitation	0.02
Histosols	192.06
Aquent	188.05
Soil layer: 30–100 cm	
Intercept	33.08
Elevation	0.05
Slope	−1.04
Aquent	359.45
Histosols	239.73
Ultisols	18.73

3.3. Spatial and vertical distribution of soil organic carbon stocks

Predicted SOC stocks of surface 30 cm and 30–100 cm layers (Fig. 3a and c) showed a large spatial variability with coefficient of variation values of 64.3% and 90%, respectively. SOC stocks of surface layer ranged from 2 to 325.7 Mg ha^{-1} and comparatively larger range of SOC stocks was observed in the subsurface (2.76 to 409.5 Mg ha^{-1}). Coastal and inland areas situated in southern to western regions had the highest predicted levels of SOC stocks throughout the profile (> 165 Mg ha^{-1}). These low-lying coastal areas represent marshy wetlands characterized with poor drainage and clayey Alluvial origin (Mapa et al., 1999). These soils belong either to Hemists or Aquents suborder. Moreover, these poorly drained soils are distributed in the wettest parts of the country (mean annual rainfall > 2500 mm). Southwestern region including the central highlands of the country (elevation > 1060 m) had the second highest predicted levels of surface (74 to 165 Mg ha^{-1}) and subsurface (76–176 Mg ha^{-1}) SOC stocks. Uniformly distributed high annual rainfall (> 2500 mm) and comparatively lower temperatures representing humid tropical climatic condition provided favorable conditions for building up of soil organic carbon stocks at these locations. Land areas distributed in the intermediate elevation zone (300 to 900 m) but receiving comparatively less mean annual rainfall (1750 to 2500 mm) had moderate level of predicted SOC stocks both in surface and subsurface soil layers (44 to 74 Mg ha^{-1}). Majority of the area of the Island had low predicted levels of SOC stocks ranging from 2 to 44 Mg ha^{-1} (Fig. 3a and e). These areas are located at low-lying (0 to 270 m) drier part of the Island with seasonally dry tropics receiving less mean annual rainfall (< 1750 mm) and high mean annual temperature (27.5 °C). Moreover, lowest SOC stocks were observed in low lying areas of southeastern and northwestern parts with the climatic region of semiarid tropics receiving lowest amount of annual rainfall (< 1000 mm). Compared to SOC stocks maps produced in this study, WISE30sec data derived maps (Fig. 3b and f) showed lower range of values in surface (26.9 to 126.5 Mg ha^{-1}) and subsurface (26.9 to 126.5 Mg ha^{-1}). However, these maps showed a considerable overestimation of SOC in low-lying (0 to 270 m) drier parts of the Island and coastal areas of the Western part of Sri Lanka where sandy soils (Quartzipsaments) are observed. Further, un underestimation of SOC was observed in the wet central highlands of the country. Estimates of SoilGrids250m (Fig. 3c and g) showed comparatively very wide ranges of SOC stocks in both surface (26.0 to 504.0 Mg ha^{-1}) and subsurface (16.0 to 1210 Mg ha^{-1}). Thus, considerable overestimation of SOC

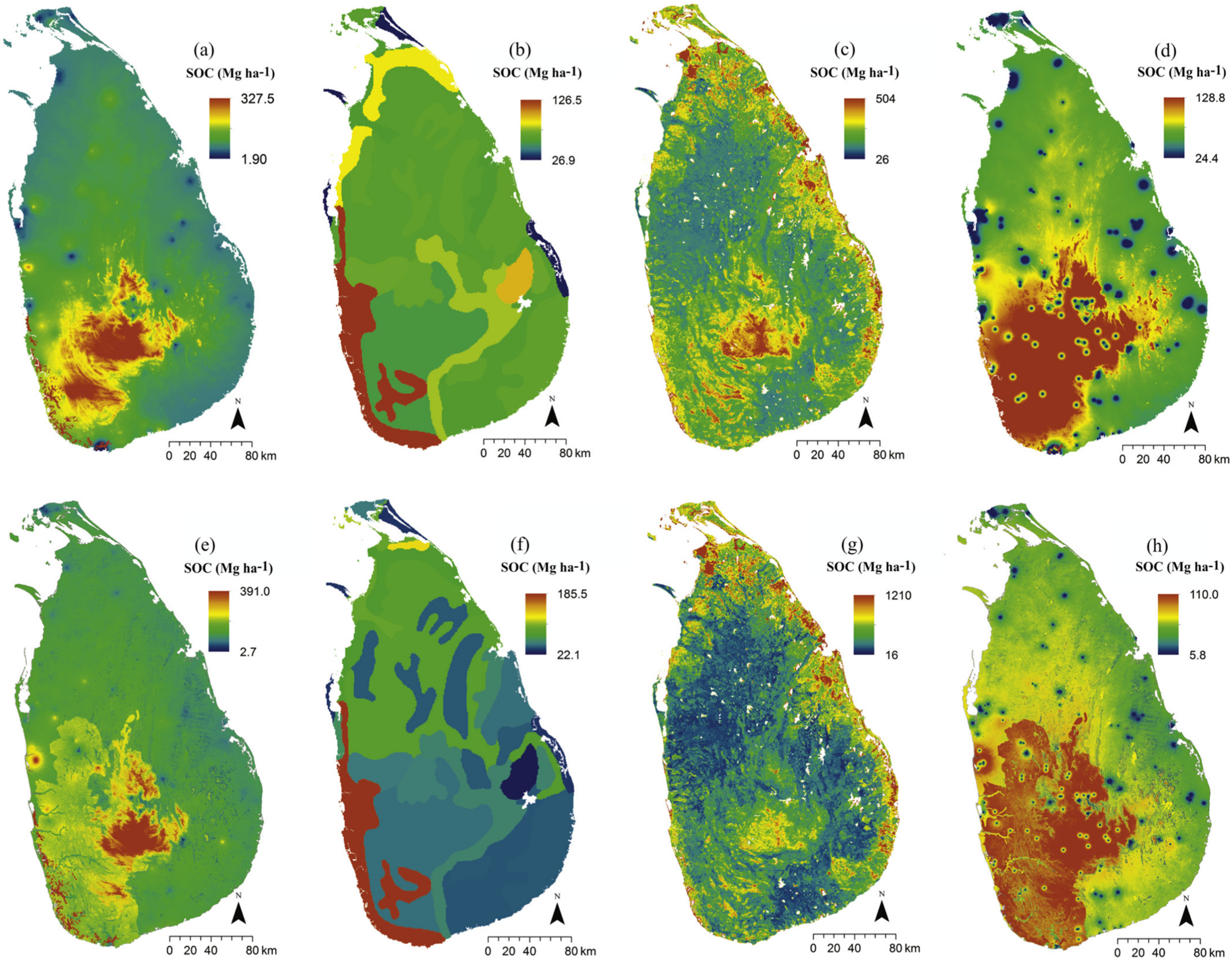

Fig. 3. SOC stocks in the surface soil layer (0–30 cm) predicted by (a) regression kriging (b) WISE30sec data, (c) SoilGrids250m, (d) 95% prediction interval of surface SOC stocks prediction and SOC stocks in the subsurface soil layer (30–100 cm) predicted by (e) regression kriging (f) WISE30sec data, (g) SoilGrids250m, (h) 95% prediction interval of subsurface SOC stocks prediction.

stocks throughout the Island was evident. Especially, sandy coastal areas of North to Northeast were estimated with large SOC stocks (> 450 Mg ha^{-1}) in both surface and subsurface layers.

Fig. 3d and h show the prediction intervals of surface and subsurface SOC stocks. Areas having higher predicted surface and subsurface SOC stocks showed larger prediction uncertainty. The inadequacy of number of samples to capture the heterogeneity of environmental controllers of SOC, topography and climatic factors could be the main reason for comparatively large uncertainty. Smaller prediction uncertainty was observed in areas with lower SOC stocks. The less heterogeneity in major controller of SOC stocks in these areas has resulted in smaller prediction uncertainty. The uncertainty analysis revealed the need of additional soil observations in the south-west to central parts of the Island to improve the accuracy of these SOC estimates. We used the following equation to compute the theoretical sample size (n) required to estimate SOC stocks at a confidence interval (CI) of 10 Mg ha^{-1}:

$$n = \frac{t^2_{(1-\alpha/2)} \times S^2}{\left(\frac{CI}{2}\right)} \tag{13}$$

where, $t_{(1-\alpha/2)}$ is the t distribution value for $\alpha = 0.05$ and S is the standard deviation of SOC stocks of surface soil (Table 1). We started calculating by specifying $n = 50$ and computed iteratively towards a stable value of t distribution. This resulted in the need of a sample size of $n = 1676$. The method suggested by Vitharana et al. (2017) can be used to spatially distribute sampling locations while representing the spatial heterogeneity of environmental controllers of SOC stocks.

After excluding surface area occupied by water bodies, the total SOC stocks in the 0–30 cm soil layer was estimated to be 255 Tg C (1 Tg = 10^6 Mg). The spatial prediction uncertainties showed that the predicted SOC stocks could range from 29 to 628 Tg C at the confidence level of 95%. The SOC stock in the 30–100 cm soil layer was estimated to be 243 Tg C and which could range from 32 to 571 Tg C at 95% probability. Our study showed a comparatively larger accumulation of soil C in the surface soils (average = 42.6 Mg ha^{-1}) in comparison to the subsurface soils (average = 40.1 Mg ha^{-1}). This study revealed that 0–100 cm soil layer of the tropical Island stored 500 Tg C, 51.5% of this magnitude is stored in the surface 0.3 m. Prediction uncertainty indicated that the total SOC storage could range from 60 to 1200 Tg C at 95% confidence level.

4. Discussion

4.1. Environmental factors controlling spatial distribution of SOC stocks

Consistent with our observations, many studies have reported

Table 3
Validation results of soil organic carbon stock (SOC) maps derived from regression kriging (RK) of profile data, SoilGrids250m and WISE30sec data bases. MEE is mean estimation error, RMSE is root mean square error and *r* is Pearson's correlation coefficient between measured and estimated SOC stocks.

SOC stock Map	Validation indices		
	MEE (Mg ha^{-1})	RMSE (Mg ha^{-1})	*r*
Soil layer: 0–30 cm			
RK	−1.60	29.5	0.8
SoilGrids250m	−41.1	61.1	0.5
WISE30sec	−7.5	45.5	0.3
Soil layer: 30–100 cm			
RK	−0.90	24.9	0.8
SoilGrids250m	−67.80	115.34	0.3
WISE30sec	−12.9	58.4	0.3

elevation as an important environmental controller of SOC stocks (Kempen et al., 2011; Mishra and Riley, 2015; Phachomphon et al., 2010). Elevation determines the vegetation, rainfall and temperature distribution of the Island, thus impacts strongly the soil C turnover rates. Further, change in elevation is also associated with slope processes such as soil erosion and deposition (Schwanghart and Jarmer, 2011; Tan et al., 2004), causing spatial heterogeneity of SOC stocks at different scales. Under temperate conditions Leifeld et al. (2005) reported increase in SOC stocks in the order of 0.75–2.1 mg g^{-1} per 100 m increase in elevation. Secondary topographic attributes, SWI and STI did not significantly control the spatial variability of SOC stocks in our study area. Our observations are in contrary to observations of Adhikari et al. (2014) and Doetterl et al. (2013), who found these topographic attributes as strong predictors of SOC stocks. Previous studies have shown important control of climatic factors on SOC stocks. It has been reported that the biological processes which drive SOC decomposition occur at slower rates at lower temperatures resulting into increase of SOC stocks (Post et al., 1982). It is well documented that within tolerable limits, the biological processes which drive SOC decomposition will be more rapid at greater temperatures. However, studies have also shown differential effects of temperature on the decomposition of soil organic matter due to biochemical differences of various pools of soil organic matter. Fang et al. (2005) reported strong positive effect of temperature on SOC decomposition while Dalias et al. (2001) reported a negative effect. However, the stepwise regression process we adopted did not select the temperature extracted from the global climatic data as a significant predictor of SOC stocks. However, the relationship between elevation and temperature ($r = -0.9$) revealed that the impact of temperature on the variability of SOC stocks has been accounted by the elevation.

Maps of soil types contain important pedogenic information which can be used for spatial prediction of soil properties. Consistent with our findings, Hoyle et al. (2013) and Murphy (2015) have also shown the importance of soil order types in determining the distribution of soil C stocks. The NDVI is an indicator of primary and ecological productivity, and it has often been used as a strong predictor of SOC (Kunkel et al., 2011). However, we found a poor relationship between NDVI and surface ($r = 0.06$) and subsurface ($r = 0.003$) SOC stocks, as a result the NDVI was not selected as a significant environmental controller in MLR models for predicting SOC stocks of Sri Lanka. Consistent with our findings, Mandal et al. (2008) reported an average SOC stock of 31.3 Mg ha^{-1} in 0–20 cm soil layer of paddy grown soils in India. Tropical home gardens play an important role in C sequestration owing to its large contribution of biomass C stock through complex mixture of vegetation types and soil C stock preserved by stable ground cover (Kumar, 2006). Home gardens occupy a considerable proportion of the land use pattern in tropics. Our observation of lower SOC stocks under conventional tillage has been well documented in earlier studies (Luo et al., 2010; Mishra et al., 2010b). Although, observed land use at profile location was found to be an environmental controller (Section 3.1) the land use data used in model selection did not confirm this finding. It is likely that the land use data at coarse resolution (250 m) was not detailed enough to capture the relationship between land use and SOC stocks. Further, we found a weak representation of the land uses of soil profile data in the global land use data we used. This highlighted the need of detailed national land use/land cover maps to support the spatial predictions of SOC stocks.

4.2. Representation of Sri Lankan SOC stocks in global SOC stock estimates

A considerable prediction uncertainty in estimates of total SOC stocks was found in this study. Prediction uncertainties were computed based on the kriging variance of the residuals and according to Webster and Oliver (2007) the limited number of observations within the search neighborhoods have resulted in large uncertainties. This showed the perseverance need of upgrading existing soil data base by incorporating more soil profile observations representing key environmental controllers of SOC. Accuracy of our predicted SOC stock estimates in comparison to maps of global SOC stocks is shown in the Table 3.

Our predictions of SOC stocks showed lowest MEE in comparison to SOC estimates of WISE30sec and the SoilGrids250m. The near zero MEE of our predictions indicated less biased estimates, thus an absence of systematic over or under estimations. Moreover, predicted SOC stocks through regression kriging showed a greater resemblance to observed values as reflected in strong linear correlation between observed and predicted values both in surface ($r = 0.8$) and subsurface ($r = 0.8$) soils in comparison to two other predictions, SoilGrids250m ($r = 0.5$ and $r = 0.3$) and WISE30sec ($r = 0.3$ and $r = 0.3$). Comparison of RMSE values revealed the highest overall accuracy of maps of SOC stocks generated in this study (Table 3). The relative improvement of the prediction accuracy of the SOC stocks in the 0–30 cm layer in comparison to SoilGrids250m and WISE30sec data derived stocks were 51.7% and 35.2%, respectively. The SOC stocks predictions of the 30–100 cm soil layer showed even better relative improvement compared to SoilGrids250m (78.4%) and WISE30sec (57.4%). These can largely be attributed to harmonized nature of the soil profile data we used, better spatial distribution of soil profiles, and the selection of most appropriate environmental covariates for spatial predictions. The spatial distribution of legacy soil profile data showed some clustering. However, presence of clusters is common in traditional soil survey based legacy data bases since the soil surveyor locate soil profiles purposively by representing spatial distribution of soil map units (Brevik et al., 2016). Webster and Oliver (2007) indicated that a clustering in random sampling could lead to a duplication of spatial information and higher density of samples could lead to a biasedness in cross-validation results. However, Heung et al. (2017) found a poor relationship between the prediction uncertainty and sample density of legacy soil profile data thus less impact on cross validation results. However, our validation results might be little optimistic due to the partial independent nature of cross-validation technique we adopted.

Compared to estimates of total SOC stocks resulted in this study, WISE30sec data derived SOC stock maps showed an 30.1% over estimation of the C stock in surface 0–30 cm (332 Tg C) and 41.2% over-estimation in 30–100 cm layer (343 Tg C). The over estimation of total SOC stocks by the SoilGrids250 SOC stocks map for the surface 0–30 cm layer was 122.4% (567 Tg C) and for the 30–100 cm layer it was 208.6% (750 Tg C). These results showed a considerable overestimation of national SOC stocks by global SOC stock estimates. WISE30sec is a harmonized data set (grid cell size 0.86 km^2) of soil properties derived using map unit delineations of harmonized word soil data base, (HWSD, FAO et al., 2012), Köppen-Geiger climatic zones and ISRIC-wise soil profile data (~21,000 profiles). A globally consistent taxotransfer procedure has been used to derive soil properties in 'soil unit/climate' clusters at depth layers up to 200 cm. Thus, SOC stock predictions

derived from WISE30sec data is partly accounted by these two covariates (soil units and climate) found to be very relevant in our study. The WISE30sec data set has delineated the study area into 22 soil/climate map units and 12 profiles (Batjes, 2015) have been used for taxo-transfer-derived organic C and bulk density values throughout the study area. Further, these 12 profiles have been recorded during different time periods from 1974 to 1997 that could lead to issues of quality and comparability of soil analytical data. Thus, coarse resolution of soil geographical data, lack of harmonization among data and lack of profile data could have resulted in higher errors in predicted SOC stocks. Further, Batjes (2015) indicated this limitation of the data set and cautioned on using the same for (sub) national level studies. Estimates of SOC stocks in SoilGrids250m has been carried out using tree-based, non-linear machine learning models for 3D modeling of soil organic carbon content, bulk density and coarse fractions while accounting non-linear local relationships between soil properties and environmental covariates. Authors have assured the high accuracy of predicted data by employing a 10-fold cross-validation procedure. Although, nearly 21,000 soil profiles have been utilized by SoilGrids250m for generating global soil maps, according to the ISRIC's profile collection and WoSIS (Batjes et al., 2017) only 12 profile observations were available for the mapping of SOC stocks of this study area. This has caused applying greater weightage for covariates for spatial predictions as reflected by over estimation of SOC stocks in low-lying but dry areas in many parts of the country including northern, northeastern and south eastern parts of Sri Lanka. This study revealed that increasing the soil profile observations and selection of most appropriate environmental covariates including more detailed pedological map units can improve the prediction accuracy of SOC stocks represented by SoilGrids250m by 52–78% for this South Asian Island. Hengl et al. (2017) stated the need of updating soil profile networks especially for Africa and Russian Federation. SoilGrids250 global data set has been initiated as a system that is being continuously updated with the incorporation of new soil profile data and other environmental covariates, our results show great potential for SoilGrids250m to be improved in order to represent national scale SOC estimates.

5. Conclusions

Spatial distribution of soil carbon stocks of Sri Lanka showed a considerable spatial and vertical heterogeneity which arise mainly due to environmental controllers; topography, precipitation, and soil types. These key environmental controllers of soil organic carbon stocks can be used to develop observation networks for monitoring changes in soil organic carbon stocks. Our analysis revealed elevation as the key environmental covariate for spatial prediction of SOC stocks in both surface and subsurface soil layers. Moreover, the pedogenic information generated by the segregation of legacy soil maps to different levels of soil taxonomy can serve as a powerful predictor of SOC stocks. A limited but harmonized data set of soil profiles produced SOC stock estimates with 35–75% relative improvement in prediction accuracy in comparison to global estimates of SOC stocks. Our results highlighted the need of data sharing to improve the global estimates of SOC stocks through efforts such as soilgrids250m and GlobalSoilMap. The tropical Island presents clear demarcation of precipitation and elevation zones, and consequently distribution zones of SOC stocks. The wettest parts of the Island belonging to humid tropics showed higher SOC stocks which is comparable to the SOC stocks of temperate countries. The Tropical Island which occupies 0.04% of the global land area stores 0.01–0.07% of total global carbon stocks to 1 m depth. To date, national level inventory of SOC stocks in Sri Lanka has not been reported. Thus, the spatially-explicit estimates of SOC stocks we report in this study, can serve as a more accurate input for process-based simulation models which intends to predict anthropogenic and climatic impacts on soil systems. Further, digital soil map layers can also improve the process of carbon budgeting and reporting in line with global initiatives of minimizing greenhouse gas emission and thus the impacts of climate change.

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